Electric Motor Temperature Prediction using Machine Learning

Project Description:

Electric motors are essential components in industrial machinery, electric vehicles, manufacturing systems, and automation processes. During operation, electric motors generate heat due to electrical losses, mechanical friction, and environmental conditions. Excessive heat can reduce efficiency, damage insulation, and even lead to complete motor failure. Therefore, monitoring and predicting motor temperature is crucial to ensure safe and reliable operation.

The aim of this project is to develop a machine learning-based system that can accurately predict the temperature of an electric motor using operational parameters such as motor speed, torque, voltage, current, and ambient temperature. Instead of relying only on physical temperature sensors, which may fail or provide delayed readings, this project uses historical data to train predictive models capable of estimating motor temperature in real time.

The dataset used in this project contains various motor performance parameters along with temperature measurements. Data preprocessing techniques such as handling missing values, feature selection, and normalization are applied to improve model performance. The dataset is then divided into training and testing sets to build and evaluate the machine learning models.

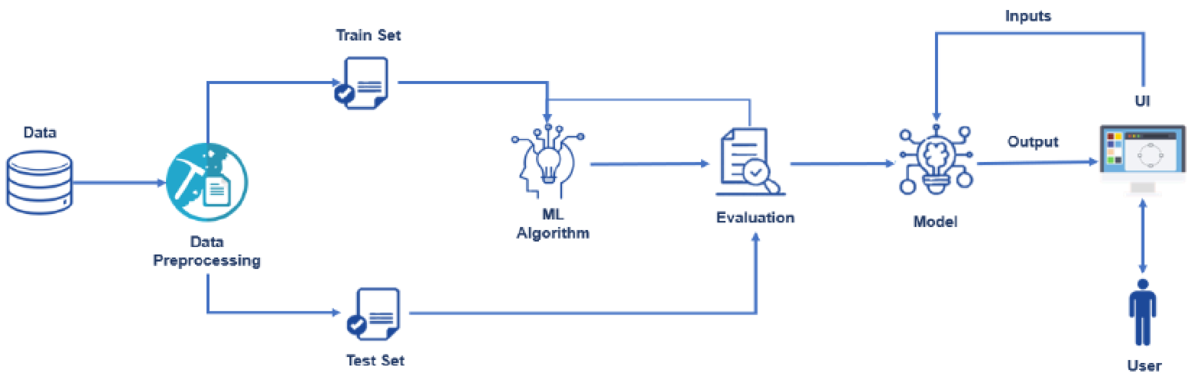
Different regression algorithms such as Linear Regression, Decision Tree, Random Forest, and Support Vector Regression can be used to perform temperature prediction. Among these methods, ensemble models like Random Forest generally provide better accuracy due to their ability to reduce overfitting and handle complex relationships between variables.

The performance of the model is evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared score (R^2). A well-trained model can accurately predict motor temperature and provide early warnings if the temperature approaches unsafe levels.

The developed system can be implemented in real-time monitoring environments and integrated with IoT devices for smart predictive maintenance. This approach helps in reducing maintenance costs, improving motor lifespan, and preventing unexpected system failures.

In conclusion, this project demonstrates how machine learning techniques can be effectively applied to predict electric motor temperature and enhance operational safety, efficiency, and reliability in industrial applications.

Technical Architecture:



Pre requisites:

To complete this project, you must required following software's, concepts and packages

- **Anaconda navigator and pycharm:**
  - Refer the link below to download anaconda navigator
  - Link : https://youtu.be/1ra4zH2G4o0
- **Python packages:**
  - Open anaconda prompt as administrator
  - Type "pip install numpy" and click enter.
  - Type "pip install pandas" and click enter.
  - Type "pip install scikit-learn" and click enter.
  - Type "pip install matplotlib" and click enter.
  - Type "pip install scipy" and click enter.
  - Type "pip install pickle-mixin" and click enter.
  - Type "pip install seaborn" and click enter.
  - Type "pip install Flask" and click enter.

    The following **software and tools** are needed:
  - Python (preferably version 3.x)
  - Google Colab or Jupyter Notebook
  - Libraries: NumPy, Pandas, Scikit-learn, Matplotlib, Seaborn
  - Dataset source (e.g., Kaggle dataset)
  - Additionally, basic knowledge of **model deployment tools** such as Flask or Gradio is helpful if the project includes building a simple user interface for temperature prediction.

Prior Knowledge:

You must have prior knowledge of following topics to complete this project.

- **ML Concepts**
  - Supervised learning: https://www.javatpoint.com/supervised-machine-learning
  - Unsupervised learning: https://www.javatpoint.com/unsupervised-machine-learning
  - Regression and classification
  - Decision tree: https://www.javatpoint.com/machine-learning-decision-tree-classification-algorithm
  - Random forest: https://www.javatpoint.com/machine-learning-random-forest-algorithm
- Supervised learning: https://youtu.be/QeKshry8pWQ?si=LlJlMbKWAsclj7t-
- Unsupervised learning: https://youtu.be/D6gtZrsYi6c?si=Dr8MdODUv6rl1qvC
- Regression: https://youtu.be/NUXdtN1W1FE?si=TEasFR_TkrSifzgo
- Evalution Metrics: https://youtu.be/YSB7FtzeicA?si=Y_y1IFWJmjxZR6VB
- Flask Basics: https://youtu.be/lj4I_CvBnt0?si=WEI0pWsUi9--EnNO

Project Objectives:

By the end of this project you will:

- You'll be able to understand the problem to classify if it is a regression or a classification kind of problem.
- You will be able to know how to pre-process/clean the data using different data pre-processing techniques.
- Applying different algorithms according to the dataset
- You will be able to know how to find the accuracy of the model.
- You will be able to build web applications using the Flask framework.

Project Flow:

the user interacts with the UI to enter the input.

? Entered input is analyzed by the model which is integrated.

? Once the model analyses the input the prediction is showcased on the UI

To accomplish this, we have to complete all the activities listed below,

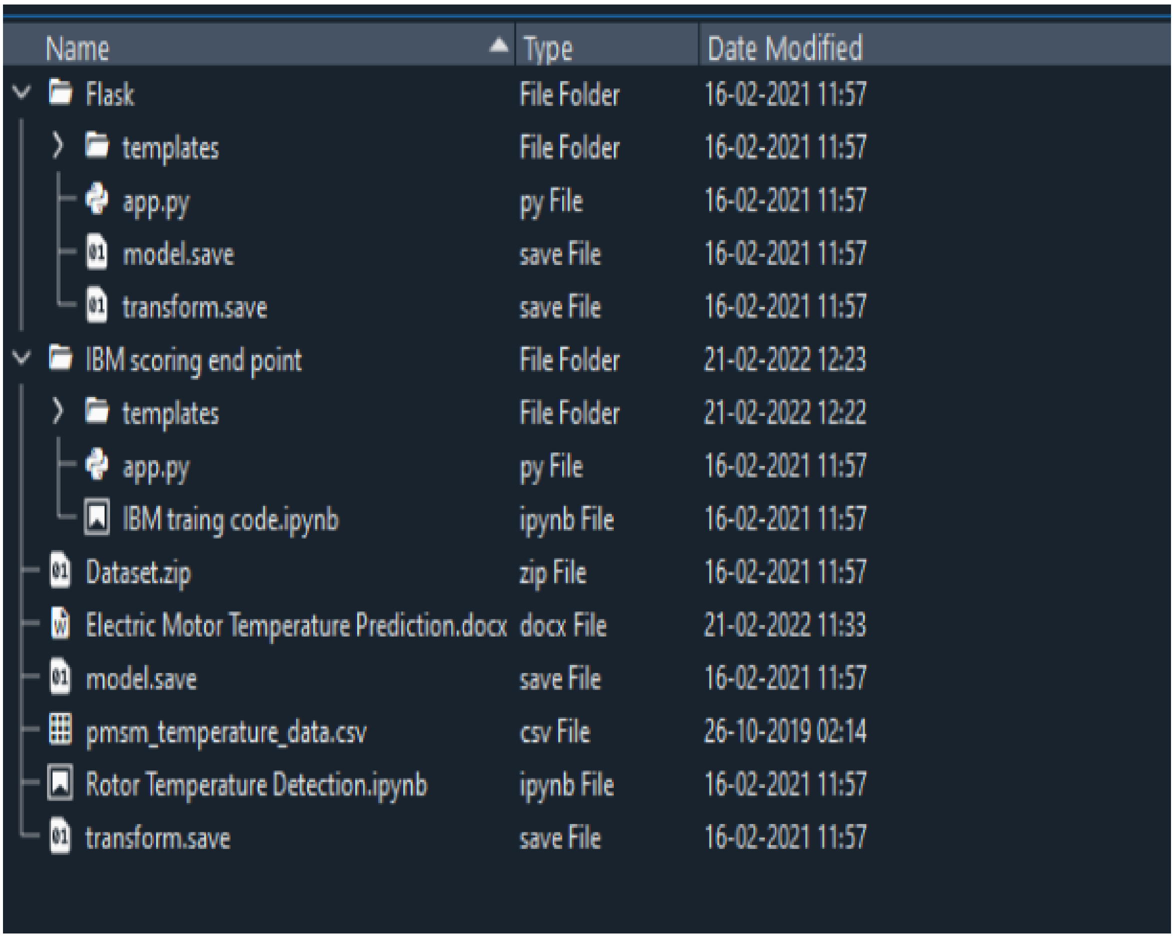
- Data collection
  - Collect the dataset or create the dataset
- Visualizing and analyzing data
  - Univariate analysis
  - Bivariate analysis
  - Multivariate analysis
  - Descriptive analysis
- Data pre-processing

- Checking for null values
- Handling outlier
- Handling categorical data
- Splitting data into train and test

- Model building
  - Import the model building libraries
  - Initializing the model
  - Training and testing the model
  - Evaluating performance of model
  - Save the model
- Application Building
  - Create an HTML file
  - Build python code

Project Structure:

Create the Project folder which contains files as shown below



Name	Type	Date Modified
Flask	File Folder	16-02-2021 11:57
templates	File Folder	16-02-2021 11:57
app.py	py File	16-02-2021 11:57
model.save	save File	16-02-2021 11:57
transform.save	save File	16-02-2021 11:57
IBM scoring end point	File Folder	21-02-2022 12:23
templates	File Folder	21-02-2022 12:22
app.py	py File	16-02-2021 11:57
IBM traing code.ipynb	ipynb File	16-02-2021 11:57
Dataset.zip	zip File	16-02-2021 11:57
Electric Motor Temperature Prediction.docx	docx File	21-02-2022 11:33
model.save	save File	16-02-2021 11:57
pmsm_temperature_data.csv	csv File	26-10-2019 02:14
Rotor Temperature Detection.ipynb	ipynb File	16-02-2021 11:57
transform.save	save File	16-02-2021 11:57

- Rotor Temperature Detection.ipynb is the jupyter notebook file where the model is built.
- Dataset.zip is the dataset file used in this project.
- model.save is the model file that generates when the notebook file is executed.

- transform.save is the transformation file used while building the model.
- Flask folder is the application folder where the web application and server-side program are present.
- IBM scoring endpoint is the folder that contains IBM training code and flask files related to IBM

Milestone 1: Data Collection

ML depends heavily on data, It is most crucial aspect that makes algorithm training possible. So this section allows you to download the required dataset.

Activity 1: Download the dataset

There are many popular open sources for collecting the data. Eg: kaggle.com, UCI repository, etc.

In this project we have used measures_v2.csv data. This data is downloaded from kaggle.com. Please refer to the link given below to download the dataset.

Link: https://www.kaggle.com/datasets/wkirgsn/electric-motor-temperature

Milestone 2: Visualizing and analysing the data

As the dataset is downloaded. Let us read and understand the data properly with the help of some visualization techniques and some analysing techniques.

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Note: There is n number of techniques for understanding the data. But here we have used some of it. In an additional way, you can use multiple techniques.

Activity 1: Importing the libraries

Import the necessary libraries as shown in the image To know about the packages refer to the link given on prerequisites..

```python
import numpy as np
import pandas as pd
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Activity 2: Read the Dataset

The dataset is read as a data frame (df in our application) using the pandas' library (pd is the alias name given to the pandas package).

```python
In [4]: df = pd.read_csv('pmsm_temperature_data.csv')
df.head()
```

	ambient	coolant	u_d	u_q	motor_speed	torque	i_d	i_q	pm	stator_yoke	stator_tooth	stator_
0	-0.752143	-1.118446	0.327935	-1.297858	-1.222428	-0.250182	1.029572	-0.245860	-2.522071	-1.831422	-2.066143	-2.0180
1	-0.771263	-1.117021	0.329665	-1.297686	-1.222429	-0.249133	1.029509	-0.245832	-2.522418	-1.830969	-2.064859	-2.0176
2	-0.782892	-1.116681	0.332771	-1.301822	-1.222428	-0.249431	1.029448	-0.245818	-2.522673	-1.830400	-2.064073	-2.0173
3	-0.780935	-1.116764	0.333700	-1.301852	-1.222430	-0.248636	1.032845	-0.246955	-2.521639	-1.830333	-2.063137	-2.0176
4	-0.774043	-1.116775	0.335206	-1.303118	-1.222429	-0.248701	1.031807	-0.246610	-2.521900	-1.830498	-2.062795	-2.0181

Activity 3: Univariate analysis

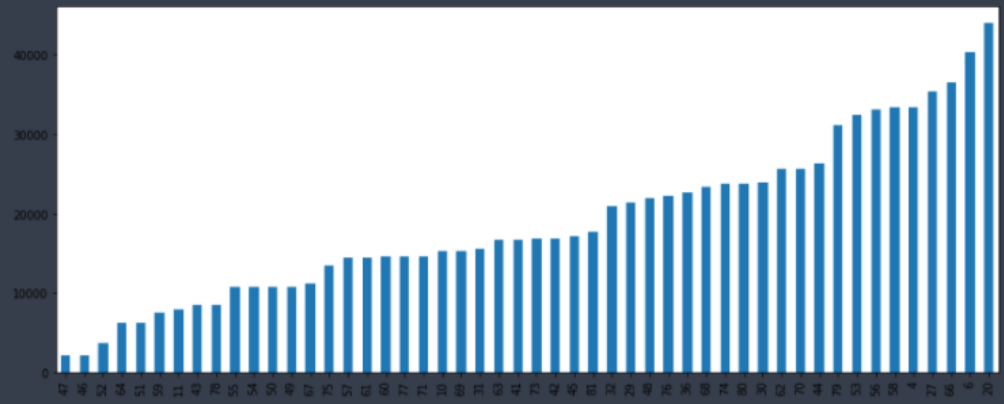
Here we get to know about our data

Bar Graph:

A bar chart or bar graph is a chart or graph that presents categorical data with rectangular bars with heights or lengths proportional to the values that they represent. The bars can be plotted vertically or horizontally.

```
In [12]: plt.figure(figsize=(15,6))
         df['profile_id'].value_counts().sort_values().plot(kind = 'bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x212d846b898>
```



As we can see, session ids 66, 6, and 20 have the most number of measurements recorded.

·Box plot:

A boxplot is a standardized way of displaying the distribution of data based on a five-number summary (“minimum”, first quartile (Q1), median, third quartile (Q3), and “maximum”). It can tell you about your outliers and what their values are.

Distribution plot:

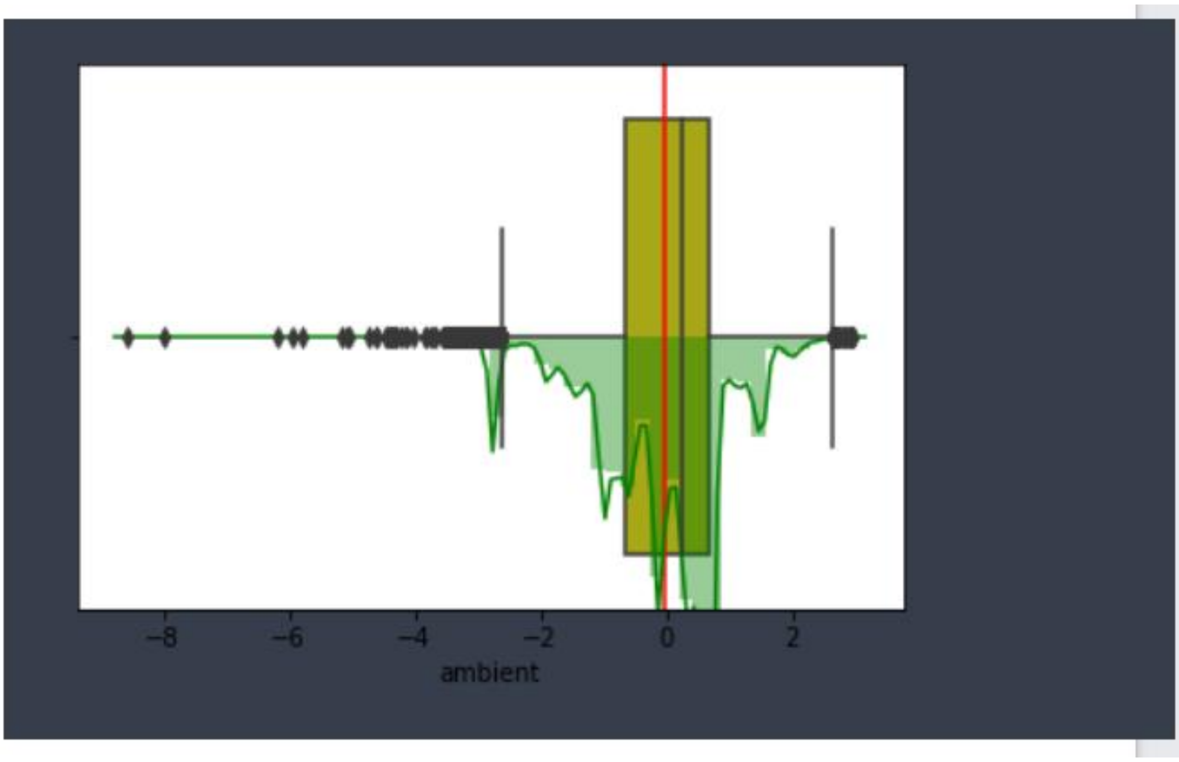
The distribution plot is suitable for comparing range and distribution for groups of numerical data. Data is plotted as value points along an axis.

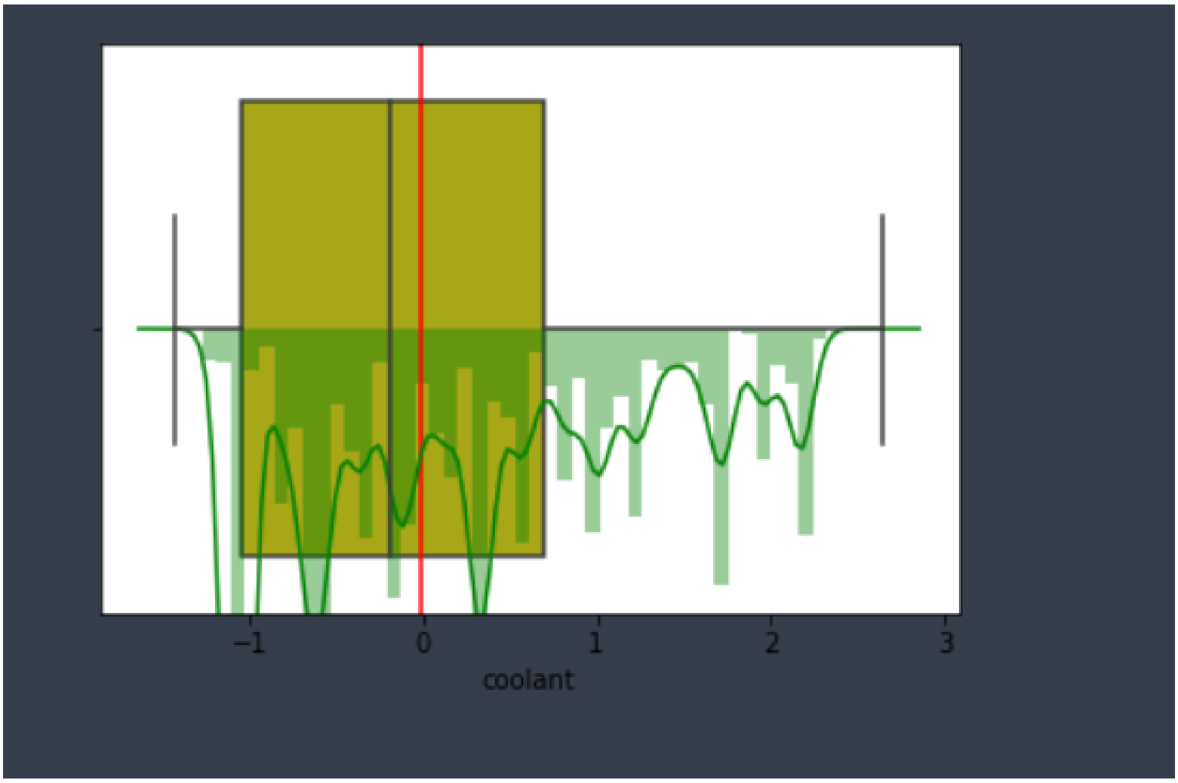
```
In [13]: df.columns
```

```
Index(['ambient', 'coolant', 'u_d', 'u_q', 'motor_speed', 'torque', 'i_d',
       'i_q', 'pm', 'stator_yoke', 'stator_tooth', 'stator_winding',
       'profile_id'],
      dtype='object')
```

```
In [14]: #Plotting Distribution and Boxplot for all the features to check for skewness
```

```
In [15]: for i in df.columns:
             sns.distplot(df[i],color='g')
             sns.boxplot(df[i],color = 'y')
             plt.vlines(df[i].mean(),ymin = -1,ymax = 1,color = 'r')#drawing the mean line
             plt.show()
```





All features boxplots are plotted and the following conclusions are drawn.

As we can see from the above plots, the mean and median for most of the plots are very close to each other. So the data seems to have low skewness for almost all variables.

Multi-variate analysis

Multivariate analysis (MVA) is a Statistical procedure for the analysis of data involving more than one type of measurement or observation. It may also mean solving problems where more than one dependent variable is analyzed simultaneously with other variables.

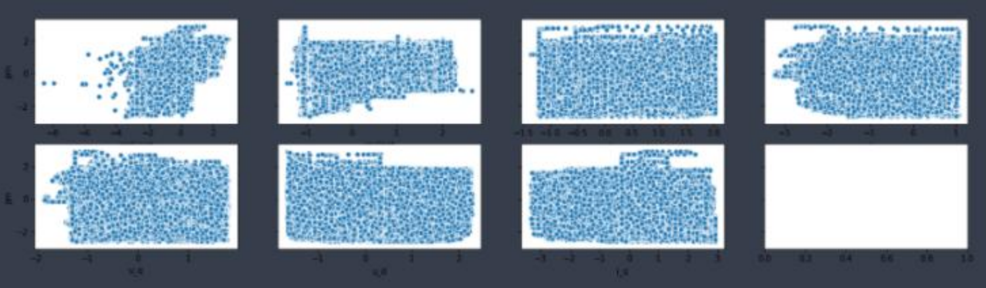
Scatterplot:

A scatter plot (also called a scatterplot, scatter graph, scatter chart, scattergram, or scatter diagram) is a type of plot or mathematical diagram using Cartesian coordinates to display values for typically two variables for a set of data.

As we want to predict the temperatures of stator components and rotor(pm), we will drop these values from our dataset for regression. Also, torque is a quantity, which is not reliably measurable in field applications, so this feature shall be omitted in this modeling.

```
In [50]:
fig, axes = plt.subplots(2, 4, figsize=(20, 5),sharey=True)
sns.scatterplot(df['ambient'],df['pm'],ax=axes[0][0])
sns.scatterplot(df['coolant'],df['pm'],ax=axes[0][1])
sns.scatterplot(df['motor_speed'],df['pm'],ax=axes[0][2])
sns.scatterplot(df['i_d'],df['pm'],ax=axes[0][3])
sns.scatterplot(df['u_q'],df['pm'],ax=axes[1][0])
sns.scatterplot(df['u_d'],df['pm'],ax=axes[1][1])
sns.scatterplot(df['i_q'],df['pm'],ax=axes[1][2])
```

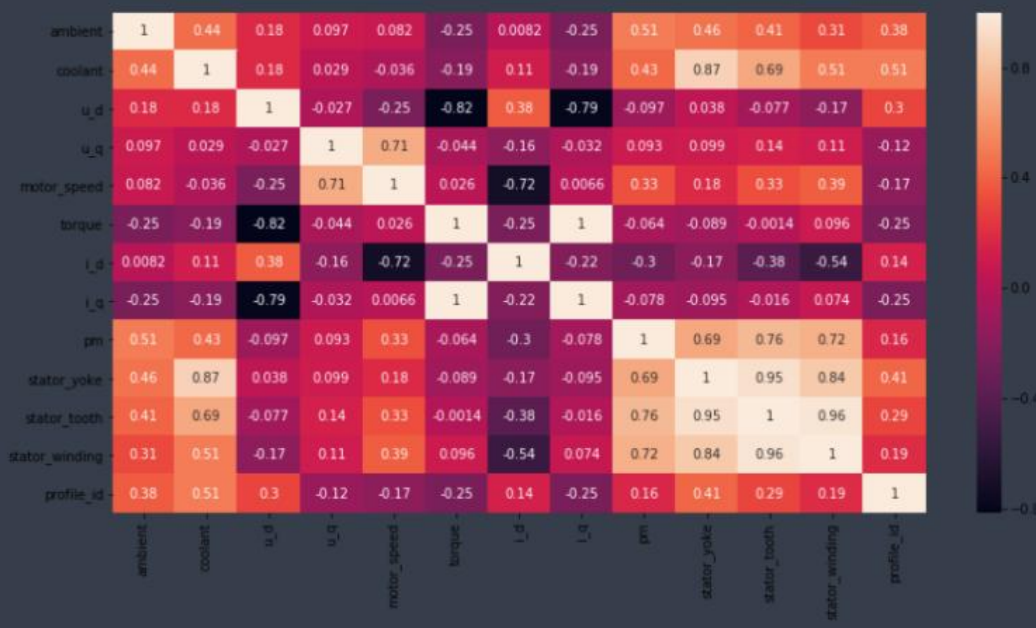
```
<matplotlib.axes._subplots.AxesSubplot at 0x212d84f4f60>
```



Heat-map:

A heat map is a data visualization technique that shows the magnitude of a phenomenon as color in two dimensions. The variation in color may be by hue or intensity, giving obvious visual cues to the reader about how the phenomenon is clustered or varies over space.

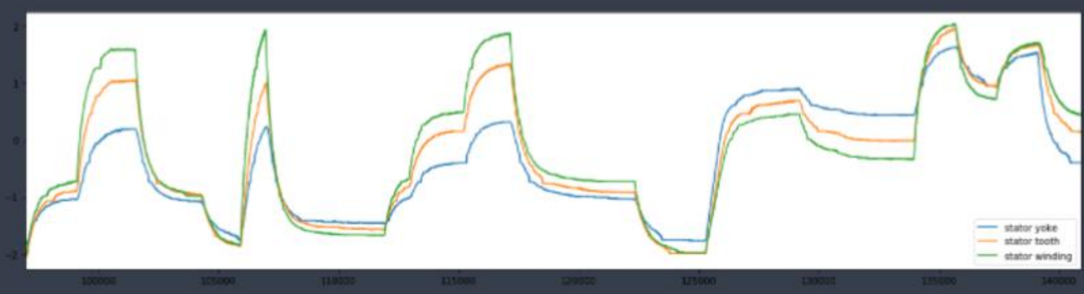
```
plt.figure(figsize=(14,7))
sns.heatmap(df.corr(),annot=True);
```



From the heatmap above, we can see that torque and q component of current are almost perfectly correlated. Also, there seems to be a very high correlation between temperature measurements of stator yoke, stator tooth, and stator windings.

For a random measurement, we can try to compare the temperatures of the 3 stator components.

```
plt.figure(figsize=(20,5))
df[df['profile_id'] == 20]['stator_yoke'].plot(label = 'stator yoke')
df[df['profile_id'] == 20]['stator_tooth'].plot(label = 'stator tooth')
df[df['profile_id'] == 20]['stator_winding'].plot(label = 'stator winding')
plt.legend();
```



- As we can see from the plot, all three stator components follow a similar measurement variance.
- As the dataset author mentioned, the records in the same profile id have been sorted by time, we can assume that these recordings have been arranged a series of times.
- Due to this, we can infer that there has not been much time given for the motor to cool down in between recording the sensor data as we can see that initially the stator yoke temperature is low as compared to the temperature of stator winding but as we progress in time, the stator yoke temperature goes above the temperature of the stator

winding.

- As profile_id is an id for each measurement session, we can remove it from any further analysis and model building.

```
In [20]: df.drop('profile_id',axis = 1,inplace=True)
         df_test.drop('profile_id',axis = 1,inplace=True)
```

Activity 4: Descriptive analysis

We'll see which particular variables contribute to the rotor temperature individually by checking their statistical significance.

Descriptive analysis is to study the basic features of data with the statistical process. Here pandas have a worthy function called describe. With this described function we can understand the unique, top, and frequent values of categorical features. And we can find mean, std, min, max, and percentile values of continuous features.

df.info():

This function is used to display a brief introduction about the data set such as the. of rows and columns, the Data type of each column, whether the null values are present in the column or not.

```
In [8]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 942677 entries, 0 to 982769
Data columns (total 13 columns):
ambient           942677 non-null float64
coolant           942677 non-null float64
u_d               942677 non-null float64
u_q               942677 non-null float64
motor_speed       942677 non-null float64
torque            942677 non-null float64
i_d               942677 non-null float64
i_q               942677 non-null float64
pm                942677 non-null float64
stator_yoke       942677 non-null float64
stator_tooth      942677 non-null float64
stator_winding    942677 non-null float64
profile_id        942677 non-null int64
dtypes: float64(12), int64(1)
memory usage: 100.7 MB
```

df.describe()

This function is used to analyze the descriptive statistics of the data such as mean, median, quartile values, maximum and minimum values of each column.

```
In [9]: df.describe()
```

	ambient	coolant	u_d	u_q	motor_speed	torque	i_d	i_q	pm
count	942677.000000	942677.000000	942677.000000	942677.000000	942677.000000	942677.000000	942677.000000	942677.000000	942677.
mean	-0.030010	-0.008238	-0.021835	0.007720	0.003210	0.020170	-0.002465	0.019958	-0.0050
std	1.007729	1.009503	0.994308	0.996054	0.996456	0.999063	1.000106	0.999683	1.00141
min	-8.573954	-1.429349	-1.655373	-1.861463	-1.371529	-3.345953	-3.245874	-3.341639	-2.6319
25%	-0.634542	-1.041886	-0.854390	-0.881885	-0.951878	-0.265042	-0.760764	-0.254672	-0.6678
50%	0.242495	-0.185147	0.225416	-0.089520	-0.140245	-0.121022	0.196713	-0.091449	0.09915
75%	0.681905	0.698607	0.356361	0.859836	0.855827	0.561778	1.013952	0.543750	0.67784
max	2.967117	2.649032	2.274734	1.793498	2.024164	3.016971	1.060937	2.914185	2.91745

Milestone 3: Data Pre-processing

As we have understood how the data is. Let's pre-process the collected data.

The download data set is not suitable for training the machine learning model as it might have so much randomness so we need to clean the dataset properly in order to fetch good results. This activity includes the following steps:

- Handling missing values
- Handling categorical data
- Handling outliers
- Scaling Techniques
- Splitting dataset into training and test set

Note: These are the general steps of pre-processing the data before using it for machine learning. Depending on the condition of your dataset, you may or may not have to go through all these steps.

In the data frame, head() function is used to display the first 5 data. Our dataset has ambient, coolant,u_d,u_q,motor_speed , i_d , i_q ,stator_yoke,stator_winding and profile_id, pm(output)

```
df.head()
```

ınt	u_d	u_q	motor_speed	torque	i_d	i_q	pm	stator_yoke	stator_tooth	stator_winding	profile_id
446	0.327935	-1.297858	-1.222428	-0.250182	1.029572	-0.245860	-2.522071	-1.831422	-2.066143	-2.018033	4
021	0.329665	-1.297686	-1.222429	-0.249133	1.029509	-0.245832	-2.522418	-1.830969	-2.064859	-2.017631	4
681	0.332771	-1.301822	-1.222428	-0.249431	1.029448	-0.245818	-2.522673	-1.830400	-2.064073	-2.017343	4
764	0.333700	-1.301852	-1.222430	-0.248636	1.032845	-0.246955	-2.521639	-1.830333	-2.063137	-2.017632	4
775	0.335206	-1.303118	-1.222429	-0.248701	1.031807	-0.246610	-2.521900	-1.830498	-2.062795	-2.018145	4

Activity 1: Drop unwanted features

As we want to predict the temperatures of stator components and rotor(pm), we will drop these values from our dataset for regression. Also, torque is a quantity, which is not reliably measurable in field applications, so this feature shall be omitted in this modeling.

Dropping the columns from the dataset is being concluded with the help of a scatter plot, which is available in the data analysis part**.**

```
df.drop(['stator_yoke','stator_tooth','stator_winding','torque'],axis = 1)
```

Activity 2: Handling missing values

For checking the null values, df.isnull() function is used. To sum those null values we use .sum() function to it. From the below image we found that the education column and previous year rating column have null values.

```
In [11]: df.isnull().sum()

ambient           0
coolant           0
u_d               0
u_q               0
motor_speed       0
torque            0
i_d               0
i_q               0
pm                0
stator_yoke       0
stator_tooth      0
stator_winding    0
profile_id        0
dtype: int64
```

There are no null values in the dataset, we can skip this step.

Activity 3: Handling outliers

With the help of a boxplot, outliers are visualized (refer to activity 3 univariate analysis). And here we are going to find the upper bound and lower bound of the Na_to_K feature with some mathematical formula.

- To find the upper bound we have to multiply IQR (Interquartile range) with 1.5 and add it with 3rd quantile. To find a lower bound instead of adding, subtract it with 1st quantile. Take the image attached below as your reference.
- If outliers are removed, we lose more data. It will impact model performance.
- Here removing outliers is impossible. So, the capping technique is used on outliers.
- Capping: Replacing the outliers with upper bound values.

Note: In our Dataset all the values are in the same range, so outliers replacing is not necessary.

Activity 4: Handling Categorical Values

As we can see our dataset has categorical data we must convert the categorical data to integer encoding or binary encoding.

To convert the categorical features into numerical features we use encoding techniques. There are several techniques but in our project, we are using feature mapping and label encoding.

Note: In our dataset, there is no categorical data type, so we can skip this step.

Activity 5: Normalizing the values

As we want to predict the temperatures of stator components and rotor(pm), we will drop these values from our dataset for regression. Also, torque is a quantity, which is not reliably measurable in field applications, so this feature shall be omitted in this modeling.

We are using minmax scaler ,which is a function in preprocessing module in sklearn library

```
mm = MinMaxScaler()
X = mm.fit_transform(X)
X_df_test = mm.fit_transform(X_df_test)
y = df['pm']
y_df_test = df_test['pm']
X = pd.DataFrame(X,columns = ['ambient', 'coolant', 'u_d', 'u_q', 'motor_speed', 'i_d','i_q'])
X_df_test = pd.DataFrame(X_df_test,columns = ['ambient', 'coolant', 'u_d', 'u_q', 'motor_speed', 'i_d','i_q
y.reset_index(drop = True,inplace = True)
y_df_test.reset_index(drop = True,inplace = True)
```

Saving the transformation

```
import joblib
joblib.dump(mm,'transform.save')

['transform.save']
```

Activity6:Splitting data into train and test

Now let's split the Dataset into train and test sets. For splitting training and testing data, we are using the train_test_split() function from sklearn. As parameters, we are passing x_resample, y_resample, test_size, random_state.

For deep understanding refer to this link

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=3)
```

Milestone 4: Model Building

Now our data is cleaned and it's time to build the model. We can train our data on different algorithms. For this project, we are applying four Regression algorithms. The best model is saved based on its performance. To evaluate the performance of the model, we use root mean square error and r-square value

Activity 1: Linear Regression

A function named LinearRegression is created and train and test data are passed as the parameters. Inside the function, the LinearRegression algorithm is initialized and training data is passed to the model with the .fit() function. Test data is predicted with the .predict()

function and saved in a new variable. For evaluating the performance of the model, we use root mean square error and r-square value**.**

Activity 2: Decision tree model

A function named decision tree is created and train and test data are passed as the parameters. Inside the function, the DecisionTreeRegressor algorithm is initialized and training data is passed to the model with the .fit() function. Test data is predicted with the .predict() function and saved in a new variable. For evaluating the performance of the model, we use root mean square error and r-square value.

Activity 3: Random forest model

A function named randomForest is created and train and test data are passed as the parameters. Inside the function, the RandomForestRegressor algorithm is initialized and training data is passed to the model with .fit() function. Test data is predicted with .predict() function and saved in new variable. For evaluate the performance of the model, we use root mean square error and r-square value.

Activity 4: Support Vector Machine model

A function named SVR is created and train and test data are passed as the parameters. Inside the function, SVR algorithm is initialized and training data is passed to the model with .fit() function. Test data is predicted with .predict() function and saved in new variable. For evaluating the performance of the model, we use root mean square error and r-square value**.**

```
In [51]: from sklearn.linear_model import LinearRegression
         from sklearn.tree import DecisionTreeRegressor
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.svm import SVR
```

```
In [52]: lr=LinearRegression()
         dr=DecisionTreeRegressor()
         rf =RandomForestRegressor()
         svm =SVR()
```

```
In [*]: lr.fit(X_train,y_train)
        dr.fit(X_train,y_train)
        rf.fit(X_train,y_train)
        svm.fit(X_train,y_train)
```

Activity 5: Compare the model

```
from sklearn import metrics

print(metrics.r2_score(y_test,p1))
print(metrics.r2_score(y_test,p2))
print(metrics.r2_score(y_test,p3))
print(metrics.r2_score(y_test,p4))

0.9698725757690718
0.47757469778170836
```

Out of all the models. The decision Tree regressor is giving an r2-score of 96%, it means the model is able to explain 96% of the data. so we will select the decision tree model and save it.

To know more about R2-score, please refer to the below link

Activity 6: Evaluating performance of the model and saving the model

Evaluating the model by using RMSE (Root Mean Squared Error)

```
In [20]: from sklearn.metrics import mean_squared_error

In [26]: print(mean_squared_error(y_test,p1))

         0.030187256377134934
```

From the above picture, we can infer that the RMSE value is 0.03, which is very low.

It means our predicted values and actual values are almost equal. The difference between actual values and predicted values is very less. so we are considering this model.

Activity 7: Save The Model

Save the model

```
In [27]: import joblib

In [65]: joblib.dump(dr,"model.save")

         ['model.save']
```

Milestone 5: Application Building

In this section, we will be building a web application that is integrated into the model we built. A UI is provided for the uses where he has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.

This section has the following tasks

? Building HTML Pages

? Building server-side script

After the model is built, we will be integrating it into a web application

Activity1:Build the python flask app

In the flask application, the user values are taken from the HTML page

```
import numpy as np
from flask import Flask, request, jsonify, render_template
import joblib
app = Flask(__name__)
model = joblib.load("model.save")
trans=joblib.load('transform.save')


app = Flask(__name__)

```

Load the home page

```python
app = Flask(__name__)

@app.route('/')
def predict():
    return render_template('Manual_predict.html')
```

Prediction function

```python
@app.route('/y_predict',methods=['POST'])
def y_predict():
    x_test = [[float(x) for x in request.form.values()]]
    print('actual',x_test)
    x_test=trans.transform(x_test)
    print(x_test)
    pred = model.predict(x_test)

    return render_template('Manual_predict.html', prediction_text=('Permanent Magnet surface temperature: ',pred[0]))


if __name__ == '__main__':
    app.run(host='0.0.0.0', debug=True)
```

Activity2: Building Html Pages:

We Build an HTML page to take the values from the user in a form and upon clicking on the predict button we get the temperature predicted. The values predicted are normalized values according to the dataset. Hence units are not considered. You can get these files from the project folder.

Building Html Pages:

For this project, create three HTML files namely

? Manual_predict.html

? Sensor_predict.html

and save them in the templates folder.

For more information regarding HTML: [Link]

Lets look how our predict.html file looks like:

Activity 3: Run the Application:

Open the anaconda prompt go to the project folder and in that go to the flask folder and run the python file by using the command “python app.py”

```
Your HTML Public Link: NgrokTunnel: "https://unentreated-adella-unmalarial.ngrok-free.dev" -> "http://localhost:5000"
 * Serving Flask app '__main__'
 * Debug mode: off
INFO:werkzeug:WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
INFO:werkzeug:Press CTRL+C to quit
```

copy the HTTP link and paste it into a browser tab.

The following page will be opened

Enter the values and click on predict button, it will predict the temperature of an electric motor